WORKING PAPER SERIES 2

2005

Kamil Galuščák and Daniel Münich:

Structural and Cyclical Unemployment: What Can We Derive from the Matching Function?

CZECH NATIONAL BANK

WORKING PAPER SERIES

Structural and Cyclical Unemployment:

What Can We Derive from the Matching Function?

Kamil Galuščák
Daniel Münich

2/2005

Printed and distributed by the Czech National Bank. Available at http://www.cnb.cz.

Reviewed by:	Michaela Erbenová	(Czech National Bank)
	Miroslav Singer	(PricewaterhouseCoopers)
	Gábor Kézdi	(CEU, Budapest)

Project Coordinator: Vladislav Flek

Structural and Cyclical Unemployment:

What Can We Derive from the Matching Function?

Kamil Galuščák and Daniel Münich *

Abstract

We explain movements in the UV space, i.e. the relationship between stocks of unemployment and vacancies known as the Beveridge curve, in the Czech Republic during 1995–2004. While the Beveridge curve is described by labour market stocks, we explain shifts in the Beveridge curve using gross labour market flows by estimating the matching function. We interpret parameter changes in the matching function during the business cycle, distinguishing cyclical and structural changes in the unemployment rate. We find that labour market flows are very good coincidence predictors of turning points in the business cycle. We show that the Czech economy already suffers from the labour market hysteresis common in many other developed market economies in the EU.

JEL Codes: E24, E32, J41, J64, C23.
Keywords: Beveridge curve, Czech Republic, matching function, panel data, structural unemployment.

---

* Kamil Galuščák, Czech National Bank (kamil.galuscak@cnb.cz), Daniel Münich, CERGE-EI (daniel.munich@cerge-ei.cz). CERGE-EI is a joint workplace of the Center for Economic Research and Graduate Education, Charles University and the Economics Institute of the Academy of Sciences of the Czech Republic.
This work was supported by Czech National Bank Research Project No. D2/2003.
We thank Michaela Erbenová, Gábor Kézdi, Jan Kmenta and Miroslav Singer for valuable comments and useful criticism, and Eva Procházková of the Department of Analysis and Statistics at the Ministry of Labour and Social Affairs for assistance with administrative data. We are responsible for all remaining errors and omissions.
The views expressed in the paper are those of the authors and not necessarily those of the Czech National Bank.

Nontechnical Summary

We interpret recent economic developments in the Czech Republic using the relationship between stocks of unemployment and vacancies known as the Beveridge curve. This approach allows us to distinguish structural and cyclical changes in unemployment. While the Beveridge curve is described by variables representing labour market stocks, shifts in and movements along the curve are driven by gross flows into and from unemployment.

We model unemployment outflows as a matching function describing matching between the searching unemployed and firms. In particular, changes in structural unemployment reflected as shifts in the Beveridge curve are identified using parameter changes in the matching function. To our knowledge this is the first study interpreting parameter changes in the matching function during the business cycle.

We present evidence of increasing labour market mismatch on the Czech labour market during the last five years. We show that the Czech labour market suffers from the kind of hysteresis common in many other developed market economies in the EU. We also show that unemployment and vacancy flows may be used as early predictors of business cycle turning points.

Despite some measurement problems, the unemployment and vacancy registry data are comprehensive, published few days after collection, and not subject to statistical revisions. Availability of these indicators is important for proper timing of countercyclical policy interventions performed by governmental institutions.

From the perspective of the limited policy tools available in a small open EU economy, the (dis)functioning of the labour market and understanding of its dynamics is becoming more important with the enlargement of the monetary union.

1. Introduction

The Czech economy has witnessed remarkable changes in aggregate activity since the 1990s. Following buoyant economic growth in the middle of the decade, a slackening of aggregate activity was observed between 1997 and 1999 (Table 1.1). The recession of 1997–1999 was characterised by huge changes in labour market flows and a consequent rapid rise in unemployment. In particular, the rate of inflows into unemployment almost doubled between 1995 and 2000, while outflows from unemployment have been steadily decreasing throughout the period. The consequent surge in the rate of unemployment was accompanied by a deceleration in the growth of labour productivity and real wages. After the recession faded, economic growth rebounded in 1999, while a renewed slowdown in activity was observed in 2001 and 2002.

Figure 1.1 provides a closer look at the labour market data and the business cycle. Periods of economic expansion are defined here as areas between consecutive turning points in the cyclical component of gross domestic product at constant prices. The economy experienced increases in the rate of unemployment and, at the same time, drops in the vacancy rate during the recessions of 1997–1999 and 2001–2002. Changes in the unemployment and vacancy rates were less pronounced in the latter recession than between 1997 and 1999. On the other hand, periods of economic expansion are associated with rising vacancies and falling unemployment. A notable exception to this kind of distinction between the phases of the business cycle is observed between mid-1999 and mid-2000 and again in late 2003, when both the unemployment and vacancy rates were increasing. This suggests rising frictions on the labour market, implying growth in the structural component of the unemployment rate in these periods. In other periods there seem to be mainly cyclical changes in unemployment.

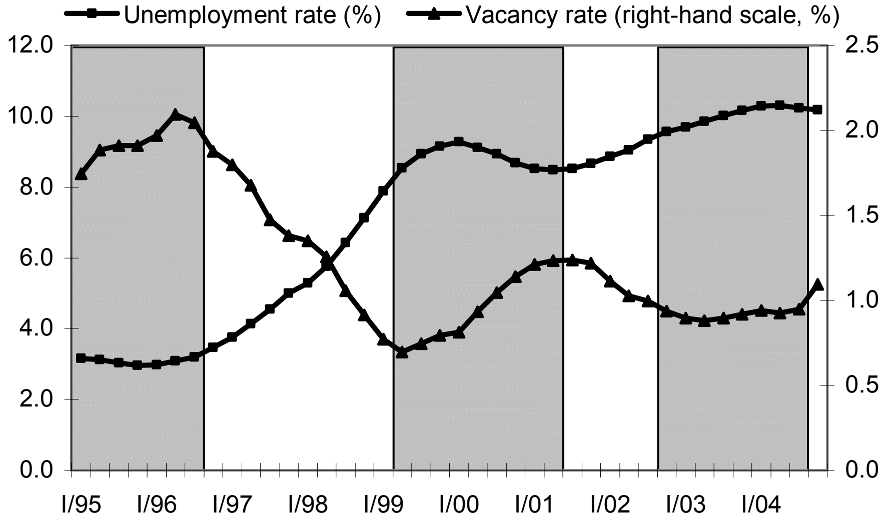
Table 1.1: Key Macroeconomic Indicators

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
GDP (%, y-o-y, real terms)										
Czech Republic		4.2	-0.7	-1.1	1.2	3.9	2.6	1.5	3.7	4.0
EU-15	2.4	1.6	2.5	2.9	2.9	3.6	1.7	1.0	0.8	2.3
Germany	1.7	0.8	1.4	2.0	2.0	2.9	0.8	0.2	-0.1	1.6
Registered unemployment rate (%, average)	3.1	3.2	4.4	6.1	8.6	9.0	8.5	9.2	9.9	10.2
Long-term unemployment rate (%, average)*				1.5	2.3	3.3	3.3	3.5	3.9	4.2
Inflow rate into unemployment (%)	0.6	0.6	0.8	1.1	1.3	1.2	1.1	1.2	1.2	1.2
Outflow rate from unemployment (%)	19.7	17.7	15.5	13.7	11.6	12.4	12.2	10.9	10.2	10.5
Vacancy rate (%)	1.9	2.0	1.6	1.1	0.7	1.0	1.2	1.0	0.9	1.0
Participation rate (%)**	86.1	85.9	86.0	85.3	85.2	84.9	85.0	85.0	84.9	85.3
Aggregate labour productivity (%, y-o-y)		2.9	0.0	0.8	4.0	4.6	2.2	0.8	4.4	4.2
Average monthly nominal wages in monitored organisations (%, y-o-y)	18.6	18.3	9.9	9.2	8.4	6.4	8.7	7.3	6.6	6.6
Average monthly real wages in monitored organisations (%, y-o-y)	8.7	8.7	1.3	-1.4	6.2	2.4	3.8	5.4	6.5	3.7

Note: Data for the Czech Republic if not specified otherwise. * May to December average in 1998. ** Aged 30–59 years.

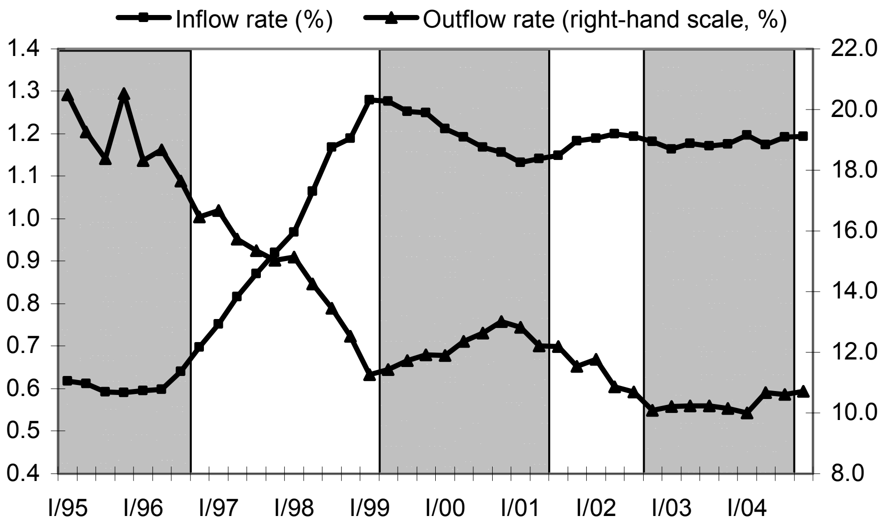
Source: Eurostat, Czech Statistical Office, Ministry of Labour and Social Affairs, own calculations.

Figure 1.1: Unemployment, Vacancies and the Business Cycle



Note: Seasonally adjusted registry data on unemployment and vacancies. Shaded areas denote periods of expansion as observed between the turning points in the cyclical component of gross domestic product at constant prices. The cyclical component is derived using the Band-Pass filter.

Figure 1.2: Unemployment Flows and the Business Cycle

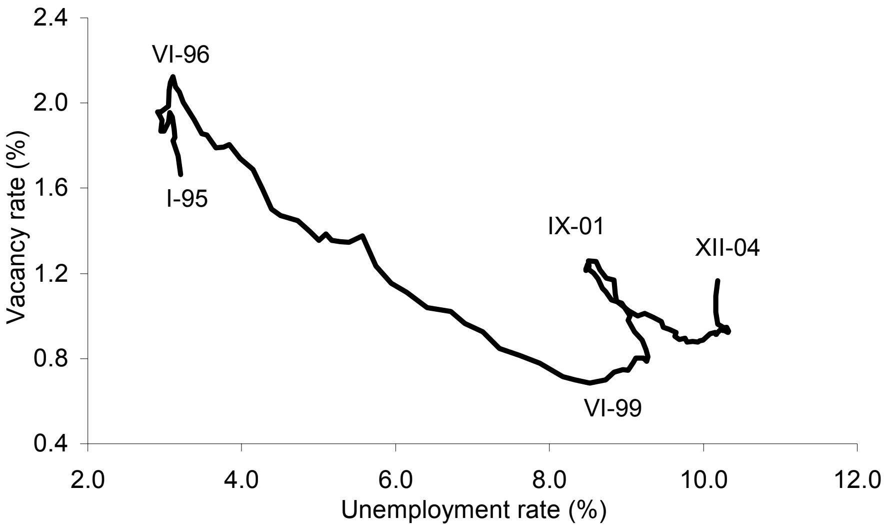


Note: Seasonally adjusted registry data on unemployment flows. Shaded areas denote periods of expansion as observed between the turning points in the cyclical component of gross domestic product at constant prices. The cyclical component is derived using the Band-Pass filter.

While the vacancy rate may be a good indicator of turning points in the business cycle, the unemployment rate follows the cycle with a certain lag (Figure 1.1). While the turning points in the cycle coincide with points of inflection in the rate of unemployment, the association with changes in unemployment flows should be even closer. This is supported by Figure 1.2, showing that the inflow rate into unemployment and the outflow rate from unemployment closely coincide with turning points in the business cycle. In particular, the economic recoveries in 1999 and 2003 were signalled by reversing trends in unemployment flows. Furthermore, the economic slowdowns in 1997 and 2001 may have been predicted by changing trends in unemployment flows. For institutions practising countercyclical policies, unemployment flows may be used as coincidence indicators of turning points in the business cycle. This is because the figures on productivity measures appear with a 3- to 9-month delay, while the information on unemployment flows is available within a few days after the end of each month.

A popular way of illustrating changes in the economy using labour market data employs the notion of the Beveridge curve, which describes the relationship between the unemployment rate and the vacancy rate (Figure 1.3). While periods of increasing aggregate demand are characterised by increasing vacancies and decreasing unemployment, the opposite is true for recessions. On the other hand, outward shifts in the UV space, i.e. simultaneous increases in the unemployment and vacancy rates, are due to increased frictions or rising mismatches in the labour market. While an increase in the number of simultaneously existing unmatched unemployed and vacancies may be due to frictions, the same outcome can be also due to higher labour market turnover. Comparing the Czech Beveridge curve to the key macroeconomic indicators in Table 1.1, we observe that the significant growth of the economy in 1995 and 1996 seems to be accompanied by a simultaneous rise in frictions. This is indicated by an outward shift in the Beveridge curve (Figure 1.3). During 1996, the economy was hit by a recession that lasted until 1999, followed by a further rise in frictions. The consequent recovery observed since 1999 was interrupted in mid-2001 by a slight decline in aggregate demand. In the aftermath of the curtailed economic growth in 2001–2002, a further deterioration in the functioning of the labour market is observed since 2003.

Figure 1.3: The Czech Beveridge Curve



Source: Ministry of Labour and Social Affairs.
Note: Seasonally adjusted monthly data, own calculations.

A number of authors have contributed to explaining the effects shifting the Beveridge curve (see, for example, Jackman et al., 1990, or, for a recent survey, Petrongolo and Pissarides, 2001). While the Beveridge curve is mapped by stock variables, the underlying changes are driven by flow variables: inflow into and outflow from unemployment. The key relationship linking outflows from unemployment with stocks of unemployment and posted vacancies is the matching function. The matching function is a similar tool of analysis as the widely used concept of the production function. Understanding regularities in flow variables is important for identifying the origins of shifts in the Beveridge curve. These shifts are associated with parameter changes in the matching function. In other words, estimates of the matching function may help to distinguish cyclical and structural changes in the unemployment rate.

This paper is aimed at interpreting recent developments in the Czech economy based on shifts in and movements along the Beveridge curve and as reflected in parameter changes in the matching function. In particular, we distinguish cyclical and structural changes in the rate of unemployment. For this purpose, we use monthly registry data on unemployment and vacancy stocks and gross flows. To our knowledge, this is the first study attempting to explain parameter changes in the matching function during the business cycle and using the Czech data on vacancy flows.[1] From the policy perspective, the registry data do not suffer from the drawbacks of the commonly used aggregate economic indicators, particularly productivity measures. Registry data are comprehensive[2], published few days after collection, and not subject to revisions. Given that the data are of high frequency, we are able to construct coincidence indicators of economic growth. It should be borne in mind, however, that vacancy flows data, reported by labour offices for the last few years only, suffer from a particular type of measurement error. For this reason in particular, the results of the paper should be interpreted with caution.

The paper is organised as follows. The next section describes the evolution of the Czech Beveridge curve using the theoretical concepts of the Beveridge curve and the matching function. Section 3 outlines the estimation strategy, while the subsequent two sections deal with the data and results. The last section concludes.

2. Stylised Facts

From the long-term perspective, many European countries have experienced simultaneous growth in unemployment and vacancies since the early 1970s. This has induced further research into the origins of this phenomenon. The stylised negative empirical relationship between unemployment and vacancies is known as the Beveridge curve (Blanchard and Diamond, 1989, Pissarides, 2000). The underlying relationship explaining shifts in the Beveridge curve is the matching function, which relates outflows from unemployment to stocks of vacancies and unemployment. The matching function allows us to describe frictions on the labour market with limited complexity in

[1] Previous studies by Münich et al. (1995, 1999), Münich (2001), Burda and Profit (1996), and Jurajda and Münich (1999) focused primarily on the issue of transition because the business cycle did not exist in its usual form yet.

[2] Statistical offices present GDP and other productivity indicators as *estimates* – approximate indicators.

the same way that the production function is a tool for describing complex productive processes. In this section, relying primarily on Berman (1997), Jackman et. al (1990), and Petrongolo and Pissarides (2001) we discuss how specific economic shocks affect the Beveridge curve and we employ this framework to explain developments in the Czech economy. We consider specific forms of the matching function and examine parameter changes in the matching function during the business cycle.

2.1 Beveridge Curve

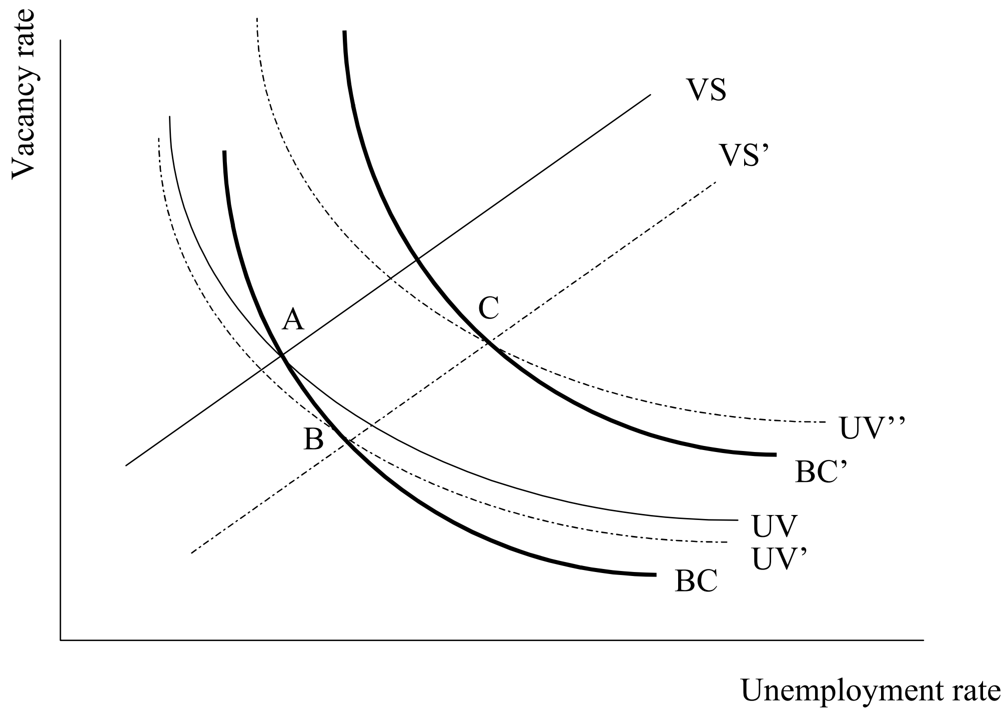
Each point on the Beveridge curve in the unemployment-vacancy space illustrated in Figure 1.3 is represented by an intersection of a downward-sloping unemployment-vacancy (UV) curve and an upward-sloping vacancy-supply (VS) curve (Figure 2.1). Given that in the steady state the flow into unemployment is equal to the outflow from unemployment, the UV curve may be characterised by a steady-state stock-flow unemployment identity as

$$u \equiv \frac{s}{s+o}, \tag{2.1}$$

while the VS curve, following Berman (1997), is described by

$$\frac{1-\lambda}{\gamma} = v\left[\frac{1}{u} + \frac{r+s}{s(1-u)}\right]. \tag{2.2}$$

Figure 2.1: Beveridge Curve



In (2.1), u is the unemployment rate and o and s are rates of outflows from and inflows into unemployment. The matching function enters (2.1) in parametric form

$$o = p(\theta)[1 - G(\alpha_R)], \qquad (2.3)$$

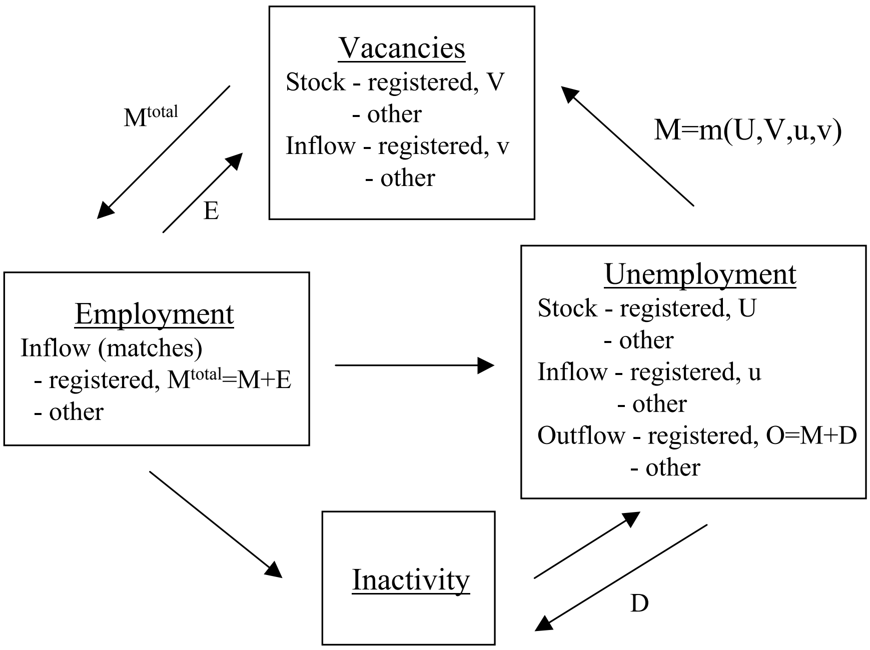
where p(.) is the rate at which the unemployed meet posted vacancies, with θ=v/u measuring labour market tightness. It is assumed that a match between an unemployed worker and a vacant job is formed only if the marginal product from the match exceeds the reservation marginal product α_R. The stochastic nature of the matching function is represented in the second term of (2.3) by a non-degenerate distribution function G(.). Its argument is

$$\alpha_R = z + \gamma_0 \theta, \qquad (2.4)$$

where z is income while unemployed and γ_0 are the search costs incurred by firms. In (2.2), r is the interest rate, λ and γ are replacement ratios between the income of the unemployed and the expected wage and between the search costs and the expected wage.

The UV curve described in (2.1) defines a steady-state rate of unemployment.[3] Provided that the inflow rate in (2.1) is constant, any change in the unemployment rate is due to changes in the outflow rate. A change in the outflow rate resulting from changes in labour market tightness corresponds to movements along a particular UV locus. On the other hand, changes in the rate at which job seekers meet with vacancies p(.) or any variation in the reservation product α_R lead to shifts in the whole UV curve.

Figure 2.2: Stocks and Flows in the Labour Market



[3] The inflow rate into unemployment and the matching function are key determinants of the unemployment equilibrium in (2.1). The matching function is contained in the denominator through (2.3). It should be noted that (2.1) is an implicit form defining the steady-state unemployment rate. For this reason, and because the labour market rarely reaches the steady state, the parameters of the matching function cannot be estimated using (2.1). We describe models of the matching function in Section 2.2 and our estimation strategy in Section 3.

While the UV curve describes the steady-state rate of unemployment, the VS curve reflects the profit-maximising behaviour of firms and employees in a given bargaining setting. A firm creates an additional vacancy if its marginal product exceeds the wage rate plus the search costs, $\alpha > w + \gamma_0$. A higher level of unemployment reduces wages through a weaker bargaining power of workers. The lower wage reduces the marginal cost of labour, resulting in additional vacancies posted by firms. These relationships lead to an upward-sloping VS curve, representing a locus of the steady-state vacancy rate.

What induces shifts in the VS curve? Consider a decrease in labour demand caused, for example, by a hike in interest rates. Higher interest rates reduce the labour demand, leading to fewer vacancies posted by firms (see equation (2.2)). This is illustrated in Figure 2.1 as a downward shift in the VS curve. However, this is not the only change in the UV space stemming from the decline in labour demand. The weaker labour market tightness decreases the reservation product (2.4) through lower search costs for workers, γ_0, and through less choosy job seekers, represented by a lower θ in (2.4). These effects entail more outflows in (2.3), depleting both stocks of vacancies and unemployment and shifting the UV curve inwards.[4] While primary movements associated with changes in aggregate demand are explained by shifts in the VS curve, there are secondary effects shifting the UV curve. The resulting path between points A and B draws the Beveridge curve displayed in Figure 2.1. Other factors shifting the VS curve downward include, for example, an increase in the effective taxation of labour or greater wage pressure resulting from an increased bargaining power of workers.

Contrary to aggregate activity shocks shifting the VS curve, structural shocks associated with changes in matching efficiency shift the UV curve. In particular, structural shocks drive outward shifts of the UV curve, as depicted by the movement from B to C in Figure 2.1. It follows from (2.3) and (2.4) that this type of shock may be caused by higher non-labour income (unemployment and welfare benefits), higher search costs or factors such as structural changes in demand or geographical or occupational mismatch. All these effects affect the probability p(.) in (2.3) with which the jobless meet unfilled vacancies and the reservation product defined in (2.4).[5] Furthermore, the UV curve shifts outwards as a result of an exogenous increase in the unemployment inflow rate, increased choosiness of the unemployed or firms, or hysteresis effects. Hysteresis effects emanate from negative duration dependence, when the skills and job search effort of the jobless decrease with the duration of their unemployment. The hysteresis following an adverse demand shock translates into an irreversible outward shift of the UV curve, as the skills and search effort of the jobless are upgraded only partially during the consequent labour demand surge.[6] It follows from Figure 1.1 that, so far, significant hysteresis effects have followed the periods of lower aggregate demand. In particular, a deterioration in the efficiency of matching

[4] This negative effect of labour market tightness on the matching process is consistent with the efficiency wage theory.

[5] The higher non-employment income also leads to higher wages through the increased bargaining power of workers, shifting the VS curve downward. While this leads to higher unemployment, the total effect of more generous welfare benefits on vacancies is ambiguous.

[6] Jackman et al. (1990) shows that hysteresis effects are a common feature of many European labour markets.

is observed in 1999–2000 and in 2003–2004, driving the long-term rate of unemployment irreversibly to higher levels (Table 1.1).[7]

2.2 Matching Function

Differentiation between particular types of shocks and associated cyclical and structural changes in the unemployment rate relies on the nature of changes in the matching function. The most general model has the form

$$M = m(U,V) \tag{2.5}$$

where the number of matches M is explained by stocks of unemployment U and vacancies V. The matching takes place in an infinitesimal time period by assumption. The most widely used form of the matching function is the Cobb–Douglas log-linear specification

$$M = AU^{\beta_1}V^{\beta_2} \tag{2.6}$$

or its logarithmic version

$$\log M = \log A + \beta_1 \log U + \beta_2 \log V. \tag{2.7}$$

In (2.5) it is assumed that all the unemployed and all vacancies are homogenous. Since job seekers may differ in their characteristics and preferences, a common extension to (2.5) introduces worker heterogeneity in terms of the reservation wage. In particular, the matching function becomes

$$M = (1 - G(w_R))m(U,V) \tag{2.8}$$

where G(.) is a non-degenerate distribution function of the reservation wage w_R. When an unemployed person meets a vacant job, the match is formed only if the wage exceeds the reservation wage. The reservation wage depends on opportunity costs (e.g. the welfare scheme) and demographic and local structures such as the youth share in the population (given that young people search with a different intensity to adults) or costs of residential moving. Comparing (2.8) to the Cobb–Douglas specification (2.6), we may infer that the effect of the reservation wage on matching is contained in the additive term in (2.6). Furthermore, the functional form (2.8) allows us to incorporate aggregate variables that influence the job search of individuals.

In (2.8) the heterogeneity of job seekers is incorporated by reservation wages. As an alternative, we may suppose that in terms of the matching probability, the characteristics of the newly unemployed differ from those among the stock of unemployed (or new vacancies from the stock of vacancies). A common extension to the matching model thus introduces flow variables. Following the notation of (2.7), we may write

$$\log M = \log A + \beta_1 \log U + \beta_2 \log V + \gamma_1 \log u + \gamma_2 \log v, \tag{2.9}$$

[7] Such changes to the structural component of the unemployment rate are consistent with estimates of the time-varying NAIRU. In particular, Hurník and Navrátil (2005) provide some evidence that the Czech NAIRU shifted from about 6.0% to about 7.5% during 1997–1999. Although their estimates are based on Labour Force Survey data, they coincide with the shifts in the Beveridge curve displayed in Figure 1.3.

where u and v are unemployment and vacancy inflows realised during a time period. Another reasoning for introducing flow variables into the matching function assumes that inflows match only with stocks while stocks match with inflows, as all the stock of vacancies is known to the stock of the unemployed from previous periods (Coles and Smith, 1998). The stock-flow matching rules out the possibility that unemployed job seekers may change their reservation wage during the unemployment spell, while, on the other hand, firms may change the wage attached to their vacancies depending on how successful they are in their recruitment search.

Existing empirical studies rely on simplified versions of the matching function such as (2.9) or (2.7) due to data limitations. These simplifications are necessary to keep the estimation tractable, but introduce potential biases. While we face similar empirical obstacles, we find expressions for possible biases and take these biases into account when interpreting our empirical findings. In order to describe these biases, we refer to Figure 2.2, showing labour market stocks and flows. Total matches, which represent the inflow into employment, are formed by vacancies registered at labour offices and by unregistered vacancies. The matches are formed by the unemployed, registered and unregistered, and by on-the-job seekers. The inactive population can match with vacancies only through unemployment, as everyone seeking a job is considered a job seeker.

As with most other studies, we have available total outflows from registered unemployment.[8] This is an imperfect measure of total matches for several reasons, as illustrated in Figure 2.2. First, unemployment outflows contain outflows into inactivity representing discouraged job seekers. Secondly, some proportion of total matches is formed by job-to-job flows. Thirdly, registered unemployment outflows underreport total outflows from unemployment as some job seekers are not registered with labour offices. Finally, some matches are formed with vacancies which are not registered at labour offices. The effect of underreported unemployed job seekers and vacancies may be removed by using first differences transformation if unregistered job seekers match only with unregistered vacancies. Estimates of the matching function comprising the registered unemployed and registered vacancies may therefore be little affected if their unregistered counterparts are omitted from the estimation.[9]

In (2.6), (2.8) and (2.9) we assume that total matches are formed by the registered unemployed and by registered vacancies. In what follows we inspect the possible effects of omitting employed job seekers and the discouraged unemployed, proceeding from Petrongolo and Pissarides (2001). We describe these effects using the stock specification (2.6) and the stock-flow model (2.9).

We have assumed that vacancies are searched for only by unemployed job seekers. If employed workers are also involved in search and job-to-job matches, their impact on the matching function depends on specific conditions. If the employed match with vacancies other than those posted at labour offices, the matching function of the unemployed is unaffected. This is the case with

[8] With total outflows in (2.7) or (2.9), the matching function enters the UV curve in (2.1), allowing us to interpret shifts in the Beveridge curve using parameter changes in the matching function.

[9] Labour offices as a marketplace serve as a specific segment of the market. Registered job seekers and registered vacancies are those who expect a non-zero probability of match. The unemployed also register to be eligible for various types of benefits.

segmented job marketplaces. Otherwise, if unemployed job seekers form a proportional number of all matches, U/(E+U), the instant rate M of matching of unemployed job seekers is

$$M = \frac{U}{E+U} A(U+E)^{\beta_1} V^{\beta_2}. \qquad (2.10)$$

On-the-job seekers compete with the unemployed for available vacancies, which is represented in the third term. Assume that the number of employed job seekers E is procyclical, so that

$$E = \lambda \left(\frac{V}{U} \right)^{\alpha}, \qquad (2.11)$$

where λ and α are positive numbers. Differentiating (2.10) with (2.11) with respect to U and V provides an insight into how the coefficients of the matching function are affected and how they change over the business cycle when E of the form (2.11) is omitted. In particular,

$$\frac{\partial M}{\partial U} \frac{U}{M} = \beta_1 + \frac{E}{E+U} (1+\alpha)(1-\beta_1) \qquad (2.12)$$

and

$$\frac{\partial M}{\partial V} \frac{V}{M} = \beta_2 - \frac{E}{E+U} \alpha (1-\beta_1). \qquad (2.13)$$

We can see that if $\beta_1<1$, the estimated coefficient of unemployment is biased upward when effects of on-the-job search are omitted, while the bias is procyclical because E/(E+U) is procyclical. On the other hand, the coefficient of vacancies is biased downward and is countercyclical if $\beta_1<1$. The impact of on-the-job search on the coefficient estimates diminishes when β_1 is close to unity. In addition, the size of the bias of the unemployment stock coefficient is greater than the bias of the vacancy stock coefficient (and exhibits a more pronounced cyclical pattern) as $1+\alpha>\alpha$.

In addition to the effect of employed job seekers on matching of the unemployed, some matches may be formed by the inflows of job searchers from inactivity. This is rather a result of inadequate measuring, as anyone entering employment is a job seeker for at least some time. Using high-frequency data, the number of direct moves from inactivity into employment may be neglected.

The second caveat related to data limitations concerns the possible presence of discouraged unemployed job seekers, i.e. the flow from unemployment into inactivity.[10] Neglecting on-the-job search for a while, total outflows from unemployment, O, comprise labour market matches and outflows of discouraged job seekers D:

$$O = M + D. \qquad (2.14)$$

Suppose that the number of discouraged job seekers is countercyclical such that

[10] In the empirical part of the paper, we estimate the matching function using total outflows instead of outflows to jobs in order to explain shifts in the Beveridge curve using parameter changes in the matching function. The link between the Beveridge curve and the matching function is given by equations (2.1) and (2.3).

$$D = U^{\gamma} V^{-\delta}, \tag{2.15}$$

where γ and δ are positive numbers. If the unemployment spell has an additional influence on D with respect to the effect of the business cycle, then $\gamma > \delta$. Neglecting the presence of discouraged job seekers leads to biases which can be expressed. Differentiating (2.14) with (2.6) and (2.15) yields

$$\frac{\partial O}{\partial U}\frac{U}{O} = \beta_1 - \frac{D}{O}(\beta_1 - \gamma) \tag{2.16}$$

and

$$\frac{\partial O}{\partial V}\frac{V}{O} = \beta_2 - (\beta_2 + \delta)\frac{D}{O}. \tag{2.17}$$

If $\gamma < \beta_1$,[11] the effect of unemployment on matches is underestimated and procyclical, while the effect of vacancies on matches is also underestimated and procyclical.

We have investigated how estimates of the stock model (2.6) may be biased when on-the-job search or discouraged job seekers are omitted and how these biases change during the business cycle. In the stock-flow specification (2.9), we may assume that discouraged job seekers recruit among the existing stock of unemployed and not among the unemployment inflow. This may be the case given that unemployment outflows out of the labour force are associated with a certain unsuccessful job search history. Therefore, omitting discouraged job seekers affects the coefficients of the stocks of unemployment and vacancies as shown in (2.16) and (2.17), while the coefficients on flows in (2.9) are not affected.

In order to describe the effect of omitting on-the-job search from the stock-flow specification (2.9), we assume that employed job seekers compete with the newly unemployed and not with the stock of the unemployed. This may be a plausible assumption, as the newly unemployed probably do not differ much from employed job seekers in terms of reservation wages. Following the notation of (2.10), the proportion of matches formed by the newly unemployed is u/(E+u), while on-the-job seekers compete with the newly unemployed, so that we may write

$$M = \frac{u}{E+u} A U^{\beta_1} V^{\beta_2} (u+E)^{\gamma_1} v^{\gamma_2}. \tag{2.18}$$

Differentiating (2.18) with (2.11), we have

$$\frac{\partial M}{\partial U}\frac{U}{M} = \beta_1 + \frac{\alpha E}{E+U}(1-\gamma_1), \tag{2.19}$$

$$\frac{\partial M}{\partial V}\frac{V}{M} = \beta_2 - \frac{\alpha E}{E+U}(1-\gamma_1), \tag{2.20}$$

[11] This may be a plausible assumption meaning that unemployment has a greater effect on the number of matches than on the number of discouraged job seekers.

$$\frac{\partial M}{\partial u}\frac{u}{M}=\gamma_1+\frac{E}{E+U}(1-\gamma_1), \tag{2.21}$$

$$\frac{\partial M}{\partial v}\frac{v}{M}=\gamma_2. \tag{2.22}$$

Assuming that $\gamma_1<1$, the unemployment stock coefficient as well as the unemployment inflow coefficient are biased upward in this case and are procyclical. If $\alpha<1$, the size of the bias and the cyclical pattern are more pronounced in the unemployment flow coefficient than in the unemployment stock. On the other hand, the vacancy stock coefficient is biased downward and is countercyclical, while the vacancy flow coefficient is unbiased and exhibits no cyclical pattern. These inferences are the same as those drawn for the stock specification (2.6) and represented in (2.12) and (2.13).[12]

In addition to the effects described by equations (2.10) to (2.22), we can consider the possibility that the reservation wage of job seekers and firms change during the business cycle. In particular, unemployed job seekers receive higher wage offers during an economic expansion for a given number of vacancies. Firms offer higher wages as it is more difficult for them to attract job seekers when the marginal product of labour is higher and firms are competing for available labour. During an expansion, to fill a vacancy with the same probability, a firm has to search for workers more intensively. As a result, the unemployed receive more job offers per unit of time for a given number of vacancies. During an expansion, when stocks of job seekers are depleted, counselling at labour offices becomes more efficient. One can also argue that during an economic boom, job seekers may be more successful in finding jobs that are not posted at labour offices. All these effects can increase the procyclical pattern of the effect of the stock of the unemployed on matches. On the other hand, the increased labour market tightness during an expansion may attract discouraged job seekers, who start competing for the same vacancies, resulting in a countercyclical effect of the unemployment stock on matches.

Higher wage offers are also directed at the newly unemployed, so we can expect to observe a procyclical dependence of the effect of unemployment flows on matches, while the other effects described in the preceding paragraph may also apply here. Following the same line of reasoning, the effect of the vacancy stock as well as the vacancy inflow on matches may be countercyclical as long as the reservation wage of job seekers rises in booms and declines in recessions.

Table 2.1 summarises the results of this subsection. Coefficient estimates for the unemployment stock and the unemployment inflow can both exhibit a procyclical pattern, primarily due to presumed changes in the reservation wage during the business cycle. The same reasoning leads to countercyclical behaviour of the vacancy stock and the vacancy inflow. Additional inferences have been drawn for how the coefficient estimates are biased and what their cyclical pattern is when on-the-job search and discouraged workers are omitted from the estimation of (2.7) or (2.9). In particular, the omission of on-the-job search leads to an upward bias in the coefficient of the unemployment stock and the unemployment flow and to a downward bias in the coefficient of the

[12] The analysis of biases is too complicated in the presence of significant correlations between the individual explanatory variables in (2.7) or (2.9).

vacancy stock, while the coefficient of the vacancy flow is unbiased. The unemployment stock and flow are procyclical, while the vacancy stock coefficient exhibits a countercyclical pattern. Regarding the effect of omitting discouraged workers from the estimation, the unemployment stock and the vacancy stock are biased downward and are countercyclical under plausible assumptions. The flow coefficients are unaffected when discouraged job seekers are omitted.

Table 2.1: Biases and Cyclical Patterns of Matching Function Coefficients

	omitting E	omitting D	reservation wage variations
U	↑,+ if $\beta_1<1$ or $\gamma_1<1$	↓,+ if $\gamma<\beta_1$	+
V	↓,– if $\beta_1<1$ or $\gamma_1<1$	↓,+	-
u	↑,+ if $\gamma_1<1$	Unbiased, no pattern	+
v	Unbiased, no pattern	Unbiased, no pattern	-

Note: ↑ upward, ↓ downward bias; + procyclical, - countercyclical pattern.

The analysis presented in this subsection suggests that the outflow into inactivity biases the estimates if the share of this outflow in the total outflow changes over time. The natural causes of these changes may be business cycle effects such as the discouraged and added-worker effects. In particular, one expects that during a recession, an increasing number of the unemployed are discouraged from search and cease to register as unemployed. The added-worker effect works in the opposite direction. While inactive people are not job seekers and thus do not fulfil the standard definition of unemployment,[13] in the Czech Republic most of them stay registered at labour offices. This is because labour offices have very limited tools to screen the willingness of the unemployed to work, and because counselling officers are reluctant to be consistent. Finally, there are strong incentives for the inactive unemployed to fake job search effort, because registration guarantees their eligibility for various types of rather generous social security benefits. This practice at labour offices overstates the actual number of unemployed by the standard ILO definition. While this practice is not fiscally efficient, it is advantageous for our analysis since it guarantees that discouraged workers are captured by the unemployment variable. Therefore, discouraged workers do not contribute to the total outflow from unemployment, at least not systematically. Discouragement of the unemployed, resulting in decreasing search intensity, decreases the efficiency and intensity of matching. This is the effect we are interested in, which is represented by shifts in the intercept parameter.[14] Being familiar with actual practices at labour offices, we are convinced that biases due to outflows to inactivity do not complicate the interpretation of parameter changes in the estimated matching function.

While the coefficients in (2.9) capture the marginal effects of job search and the search for workers, the additive constant term aggregates all other effects that are not captured by the marginal effects. The additive term thus indicates changes in the structural component of

[13] According to the International Labour Organization (ILO) definition, a person is considered unemployed if he has no paid job, is an active job searcher, and is able to accept a job offer.

[14] The statistical evidence on inactivity based on the Labour Force Survey is in line with our arguments. The participation rates shown in Table 1.1 do not indicate any clear relationship between the business cycle and aggregate participation during the business cycle we study. Furthermore, no clear cyclical pattern is observed in the ratio of the number of discouraged persons to the population in the same age group.

unemployment or, in other words, in the mismatch. On the other hand, the coefficient estimates in (2.9) reflect the effects of the business cycle.[15] Given that the unemployment inflow rate is constant, changes in the additive term of the matching function may be associated with shifts in the Beveridge curve. Conversely, changing unemployment inflows may also explain movements in the Beveridge curve, but they cannot affect our interpretation of parameter changes in the matching function.

3. Estimation Strategy

The matching function of the form (2.9) describes continuous matching and is defined for a continuous time framework. An estimable version of a matching function relies on discrete-time approximation thereof. Time aggregation is associated with several problems. For a particular time period, stocks are averages during the period while flows are sums over the period. During the time period, stocks of unemployment and vacancies are depleted by matches realised during that period, introducing a correlation between the stocks and the error term. As a remedy to this problem, lagged stocks are often used as explanatory variables. The lagged stocks are, however, imperfect measures of current stocks, resulting in biased estimates. This kind of measurement error in the explanatory variables may be removed by first differences given that the error has an additive form and is time persistent. Furthermore, the dependent variable is also measured with errors due to time aggregation. In particular, the number of matches in a given time period includes matches from the initial stocks as well as from the inflow over the time period. In order to tackle this problem, the explanatory variables of the matching function should include some proportion of unemployment and vacancy inflows. The inflows are already included in (2.9).

The problems introduced by discrete-time approximation can be mitigated to a great extent by using high-frequency data. Using high-frequency data reduces the role of direct moves from out of the labour force into employment as described in the preceding section. In particular, everyone transiting into employment becomes a job seeker for at least some time. The occurrence of transitions from out of the labour force into employment may therefore be viewed as a consequence of discrete-time approximation.

The matching function (2.9) is defined for a closed labour market. It is assumed that job seekers meet with all the vacancies in the labour market. This is unlikely in the economy-wide labour market, but may be the case in regions that can be viewed as closed labour markets. Suppose that we estimate the matching function using region-level data. If there are interactions between the regions in terms of matching, doubling the size of the labour market leads to more than two times more matches, implying higher returns to scale as compared to region-level matching.[16] It is

[15] The additive term probably captures some of the effect of omitting discouraged job seekers. In particular, a decrease in total outflows may indicate an increasing mismatch, which implies that the ratio of inactivity to employment outflows increases. When discouraged job seekers are omitted and total outflows are used in the estimation, the estimated decrease in the additive term underestimates the deterioration in matching.

[16] Consider, for example, two urns – representing local labour markets – each containing two balls. In each urn, one match may be formed. After pooling the two urns, six matches may be formed if mutual interactions are allowed, while only two matches may appear if there are no interactions between the two urns.

therefore advisable to use such a geographical level of aggregation for which the mutual interactions in matching can be neglected.[17]

The matching function (2.9) defines matches, while the steady-state unemployment rate (2.1) contains outflows from unemployment. On that account, given the data limitations, we have to assume that all outflows from unemployment result in job placements through registered vacancies and that there is no on-the-job search.[18] An estimable version of the log-linear matching function (2.9) may be written as

$$\log o_{it} = \beta_1 \log U_{i,t-1} + \beta_2 \log V_{i,t-1} + \gamma_1 \log u_{it} + \gamma_2 \log v_{it} + \alpha_i + \varepsilon_{it} \qquad (3.1)$$

where o_{it} is the number of persons leaving unemployment in region i during the time period t, $U_{i,t-1}$ and $V_{i,t-1}$ are the stocks of unemployed persons and vacancies at the end of period t-1 (the beginning of period t), u_{it} is the number of persons entering the pool of the unemployed (inflows into unemployment during t), v_{it} is the number of new vacancies (vacancy inflows), and α_i are region-specific fixed effects.

In order to remove spurious scale effects associated with heterogeneous district size, we divide all the variables by the district-specific labour force. The labour force is time-invariant by assumption.[19] As shown by Münich et al. (1999), spurious scale effects appear if the variance in district size translates to variance in the explanatory and explained variables in the regression. In such a case, the variance in district size, albeit having no economic impact, biases the estimated coefficients toward a value of one.[20]

Applying first differences to (3.1) removes region-specific fixed effects and spurious scale effects at the same time. In particular, denoting $\Delta\log o_{it}=\log o_{it}-\log o_{i,t-1}$, $\Delta\log U_{i,t-1}=\log U_{i,t-1}-\log U_{i,t-2}$, etc., we have

$$\Delta \log o_{it} = \beta_1 \Delta \log U_{i,t-1} + \beta_2 \Delta \log V_{i,t-1} + \gamma_1 \Delta \log u_{it} + \gamma_2 \Delta \log v_{it} + \Delta\varepsilon_{it}. \qquad (3.2)$$

In equation (3.2), $\Delta\log U_{i,t-1}$ and $\Delta\log V_{i,t-1}$ are correlated with the error term $\varepsilon_{i,t-1}$ through $o_{i,t-1}$ from (3.1) and the relation $U_{i,t-1} \equiv U_{i,t-2}+u_{i,t-1}-o_{i,t-1}$ (the same applies for $V_{i,t-1}$). Instrumental variables are therefore needed to prevent endogeneity biases. Our choice might prefer instruments such as lagged inflows into unemployment and the inflow of vacancies from own and adjacent regions (Wooldridge, 2001).

[17] Burda and Profit (1996) extended the matching function by introducing regional spillovers. They presuppose that the effect of adjacent districts on local matching depends on the road distance between the district capital cities. They estimated the matching function with regional spillovers for 76 Czech districts and found that unemployment in neighbouring districts has a statistically significant effect on local matching. Another approach was used by Petrongolo and Wasmer (1999). They introduced cross-sectional spillovers, allowing each worker to search in his own and other regions with different search intensities. They estimated the matching function for Britain and France and found that the search intensity is positive and significant in adjacent districts, although it is only about 10 per cent of the level of the search intensity in the region of residence.

[18] What happens when one omits the role of discouraged workers and employed job seekers is described in the preceding section.

[19] The pace at which the labour force changes is much lower than the variability of the stock and flow variables.

[20] Spurious scale effects are also removed by applying differences to the log-linear specification.

The estimation of (3.2) using ordinary least squares with appropriate instruments for $\Delta \log U_{i,t-1}$ and $\Delta \log V_{i,t-1}$ is a standard approach used in the literature. However, the estimation suffers from autocorrelation of residuals. In particular, we may surmise that the internal composition of both unemployment and vacancy stocks changes little over time. If, for example, a bunch of hard-to-match workers arrives into unemployment in a given period, it is likely to affect outflows in the current and subsequent time periods. This duration dependence appears in the estimation as serially correlated residuals. Furthermore, the serial correlation is magnified by using high-frequency data. In order to obtain efficient and unbiased estimates, we can drop the first few lags among the instruments and retain only further lags as valid instruments.[21]

In order to examine changes in the coefficients during the business cycle, we estimate (3.2) in moving windows, i.e. over a particular fixed time span that moves period by period. Within the estimation window, the regression imposes restrictions on constant coefficients over time. With coefficient estimates at hand, we can calculate the district-specific fixed effects. For average values of variables in the particular estimation period denoted with superscript j, the fixed effects in district i are computed as

$$\overline{\alpha_i^j} = \overline{\log o_{it}^j} - \beta_1^j \overline{\log U_{i,t-1}^j} - \beta_2^j \overline{\log V_{i,t-1}^j} - \gamma_1^j \overline{\log u_{it}^j} - \gamma_2^j \overline{\log v_{it}^j}\,, \qquad (3.3)$$

where means are calculated over the period j. The district fixed effects may be aggregated into an economy-wide parameter

$$A^j = \sum_i w_i \overline{\alpha_i^j}\,, \qquad (3.4)$$

where weights w_i are district labour force shares, such that $\Sigma w_i=1$.[22]

It follows from (2.1) and (2.3) that changes in the unemployment rate are directly associated with parameter changes in the matching function when the inflow into unemployment is stable, as is our case. Changes in the parameter A thus capture movements in the UV curve illustrated in Figure 1.3. In particular, A in (3.4) traces secondary effects during changes in aggregate demand and all improvements or any deterioration in the efficiency of matching. The parameter A captures the average rate of matching, while the coefficient estimates express the marginal rate of matching. For example, the coefficient on the unemployment (vacancy) stock in (3.2) determines the percentage change in the outflow from unemployment as a result of a 1 per cent change in the number of the unemployed (vacancies). The same interpretation applies to the coefficients on unemployment and vacancy inflows. The coefficient estimates contain the effects of the business cycle as well as the effects related to the omission of on-the-job search and discouraged workers.

[21] As an alternative, we can estimate a dynamic model including lagged dependent variables on the right-hand side. This remedy is not preferred because lagged dependent variables require a larger set of instruments.

[22] Equations (3.3) and (3.4) refer to the logarithm of district and aggregate fixed effects.

4. Data

The district-level data on registry unemployment and vacancies come from the registers of 77 district labour offices in the Czech Republic and represent detailed and standardised monthly sources of information collected for the Ministry of Labour and Social Affairs. The data include end-of-month values of stock variables and period-cumulative values of gross flows of unemployment and vacancies. We exclude the districts Prague, Prague-East and Prague-West from the data, because their labour markets are too specific. This leaves us with data on 74 districts.[23]

The registry unemployment data are likely to underestimate the actual number of the unemployed. Some people do not register with a labour office when they change jobs. Underreporting is more likely in urban areas, where other channels of job search are used. The underreporting is consequently likely to be uneven across districts. Assuming that the differences in the underreporting of unemployment across districts are time-invariant, this effect is removed by the differences used in this paper. In contrast to this problem, the registry unemployment might be overreported, since some people register with a labour office in order to be eligible for social security benefits. Again, we assume that this effect is to a great extent removed by first-specific differences. The vacancy data are also underreported, as some vacancies may not be registered at labour offices. All the data limitations are described in other sections of the paper.

5. Results

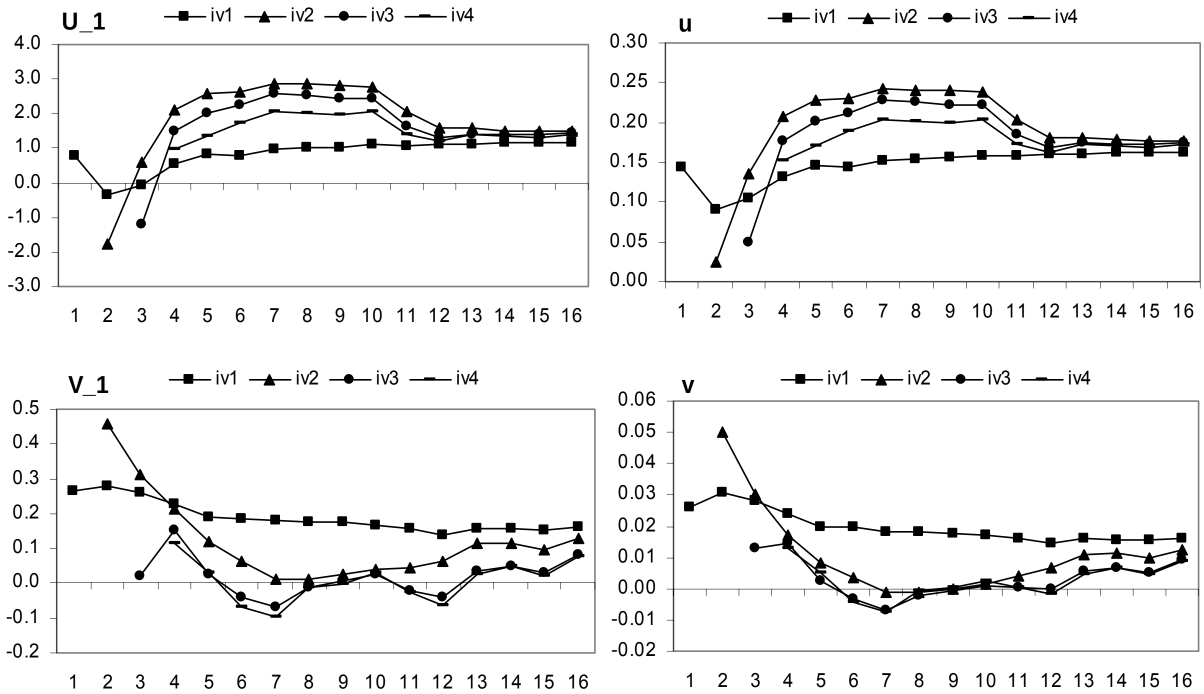
Parameter changes in the matching function have direct consequences allowing us to distinguish cyclical and structural changes in the unemployment rate given that the inflow rate into unemployment does not change (see (2.1) and (2.3)). Actually, the inflow rate into unemployment has been stable since 2000 (see Table 1.1). With respect to that, and due to data availability, we estimate (3.2) for 74 districts in the period between January 2000 and December 2004. We estimate the matching function over a fixed time span covering 13 months that moves period by period, i.e. between January 2000 and January 2001, between February 2000 and February 2001, etc. We use estimation periods that are as short as possible in order to be able to trace accurate positions of the economy in the business cycle. On the other hand, the need for a sufficient number of degrees of freedom in the estimation requires a longer panel. The choice of the length of the time span is arbitrary and the results are robust to that choice.

In the first step we select an appropriate set of instruments. As instruments we use lagged inflows of unemployment and vacancies from own and adjacent districts. We find that the presence of serial autocorrelation leads to sizeable changes in the coefficient estimates as the number of lags

[23] An inspection of the Labour Force Survey data reveals that 12.2% of employed persons in our sample were commuting to other districts in the first quarter of 2001. Restricting the sample to 66 districts with a share of commuters of less than 25% in each district, we repeated the estimation of the matching function, as described in the next section. The results are almost the same as in the case of the full sample of 74 districts. This justifies our choice of geographical level for the estimation.

rises (Figure 5.1). In order to mitigate the effect of autocorrelation on the coefficient estimates, we use as many as 16 lags. We also drop the first few lags from the set of instruments since they are most probably infected by the autocorrelation. This is illustrated in Figure 5.1. Using up to 16 lags, the size of the coefficient estimates becomes similar for instruments lagged 1 to 16 and for lags 4 to 16. Therefore, we estimate (3.2) with instruments lagged 1 to 16 and with lags of the order 4 to 16 as an alternative.

Figure 5.1: Choosing the Appropriate Set of Instruments

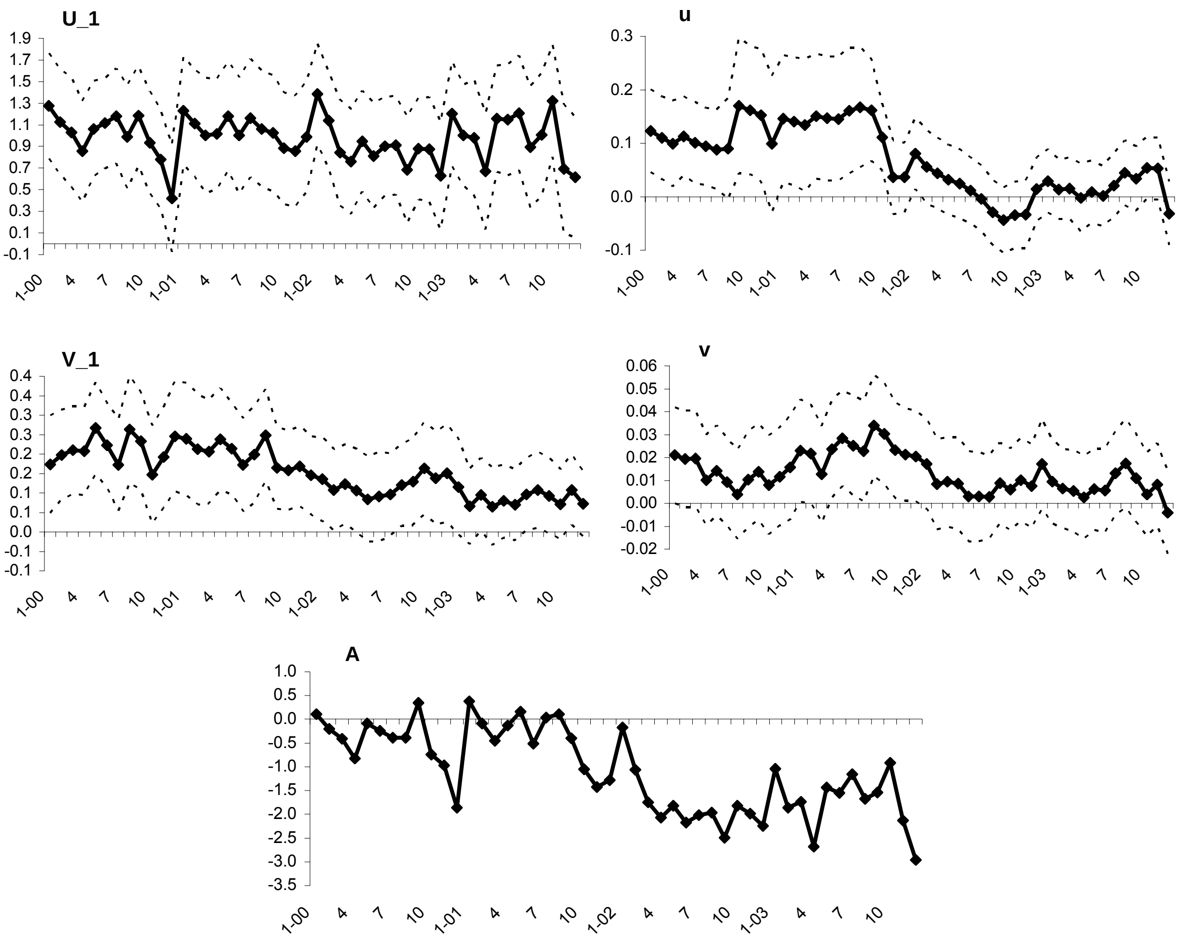


Note: Equation (3.2) is estimated over the period January 2000 – January 2001. Results for unemployment stock (U_1), unemployment inflow (u), vacancy stock (V_1) and vacancy inflow (v). The instruments include lags in the unemployment inflow and lags in the vacancy inflow from own and neighbouring districts. The set iv1 starts from the first lag, iv2 from the second, iv3 from the third and iv4 from the fourth lag. The order number of the last lag used is on the horizontal axis, while the size of the coefficient estimate is on the vertical axis.

Figure 5.2 shows the coefficient estimates of (3.2) estimated in moving windows from January 2000 – January 2001 until December 2003 – December 2004. In each panel, the horizontal axis shows the starting points of the estimation periods. The set of instruments consists of lags of the order 1 to 16 of inflows of unemployment and vacancies from own and adjacent districts. The last panel shows the aggregated fixed effects calculated using (3.3) and (3.4). Figure 5.3 depicts the same results as Figure 5.2 but with the alternative set of instruments with lags of the order 4 to 16.

The coefficient estimates of the unemployment stocks are high and close to unity. The cyclical pattern in the coefficients is less obvious, although some procyclical behaviour may be traced in Figures 5.2 and 5.3. The vacancy stock estimates are much smaller, between 0.1 and 0.3. Contrary to expectations, these estimates are not countercyclical. The size of the estimates of the unemployment inflow is between zero and 0.15, while it may exhibit a stronger cyclical pattern than the unemployment stock. On the other hand, the estimates of the vacancy inflow are negligible and almost always insignificant.

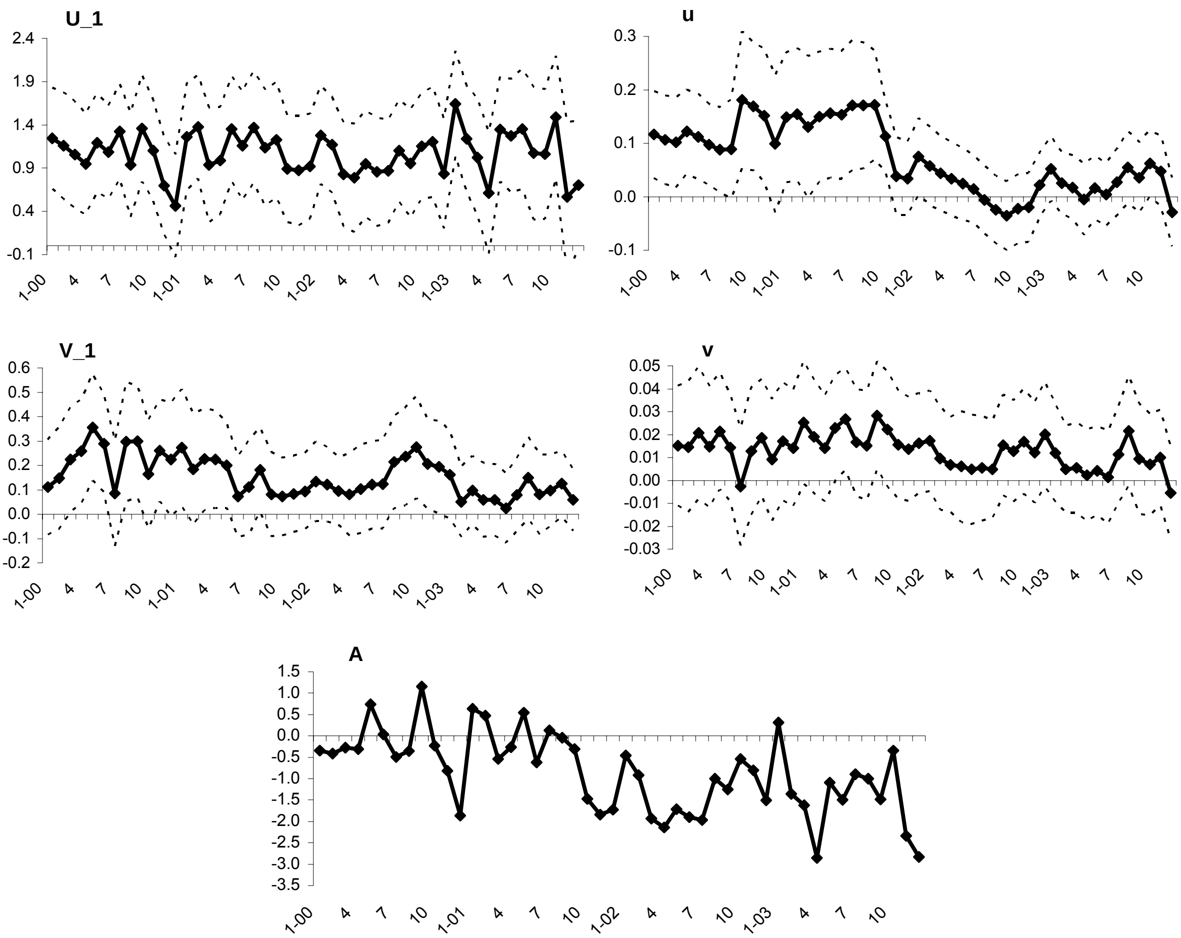
Figure 5.2: Matching Function Estimates



Note: Equation (3.2) is estimated in rolling windows spanning 13 months starting at January 2000 – January 2001 and ending at December 2003 – December 2004. Results for unemployment stock (U_1), unemployment inflow (u), vacancy stock (V_1) and vacancy inflow (v). The horizontal axis refers to the starting points of the estimation windows. The size of the coefficient estimates is on the vertical axis. The unemployment rate is instrumented using inflows of unemployment and vacancies from own and adjacent districts lagged 1 to 16. The 95 per cent confidence intervals are shown.

In order to examine the effect of omitting discouraged job seekers on the estimates, we estimated (3.2) for job placements as a dependent variable instead of all outflows from unemployment. The results are very similar to those in Figures 5.2 and 5.3 as for how the estimates change across the estimation periods. While the size of the coefficient estimates for the flow variables does not differ significantly, the coefficients of both unemployment and vacancy stocks are 20% greater than in the case of the total outflows reported in Figure 5.2. This supports our findings in (2.16) and (2.17) and presented in Table 2.1 that $\gamma<\beta_1$ in (2.16) and that the unemployment and vacancy stocks are biased downward due to the omission of discouraged job seekers. However, this is not confirmed using the alternative set of instruments. These results therefore support our arguments that the effect of omitting discouraged job seekers from the analysis is minor.

Figure 5.3: Matching Function Estimates with the Alternative Set of Instruments



Note: Equation (3.2) is estimated in rolling windows spanning 13 months starting at January 2000 – January 2001 and ending at December 2003 – December 2004. Results for unemployment stock (U_1), unemployment inflow (u), vacancy stock (V_1) and vacancy inflow (v). The horizontal axis refers to the starting points of the estimation windows. The size of the coefficient estimates is on the vertical axis. The unemployment rate is instrumented using inflows of unemployment and vacancies from own and adjacent districts lagged 4 to 16. The 95 per cent confidence intervals are shown.

The coefficient estimates for the unemployment stock are much higher than the estimates for the vacancy stock, implying that the former may be biased upward and the latter downward due to the omission of on-the-job search. In accordance with our expectations, the unemployment stock exhibits some procyclical dependence, while the cyclical pattern may be more pronounced in the unemployment inflow.[24] This complies with our expectations regarding the possible effects of omitting on-the-job search from the estimation or effects related to changes in reservation wages during the business cycle. The unemployment inflow coefficient in particular may be used as an indicator of cyclically induced changes in matching. When interpreting the results, we should bear in mind that the estimation windows cover as many as 13 months. Although the unemployment

[24] The mutual correlations of the right-hand-side variables in (3.2) are low, indicating that the interpretation of the results and their biases is not complicated.

inflow coefficient had been rising at least since the beginning of 2000, it started to fall in late 2001 after the recession effects in matching prevailed. The coefficient started to rise again in 2003, probably due to the economic recovery in 2003–2004. Nevertheless, the coefficient remains insignificant since 2002, so these results should be interpreted with caution.

Contrary to our expectations, the coefficient estimate for the vacancy stock is not countercyclical. Starting at about 0.3 in 2000 and 2001, it dropped to 0.1 throughout 2002, where it remains and is statistically insignificant. The size of the coefficient confirms our expectations that it may be biased downward as a result of omitting on-the-job search. On the other hand, the evolution of the vacancy stock coefficient may point to a deterioration in the role of registered vacancies in the matching process. Finally, the coefficient estimate for the vacancy inflow is small and insignificant. Its pattern is difficult to interpret. Vacancy coefficients perform very badly, indicating a worsening in the functioning of the Czech labour market during recent years.[25] On the other hand, they suggest possible data problems.[26]

The last panels in Figures 5.2 and 5.3 contain estimates of the parameter A. The parameter was almost constant in 2000 and 2001, but dropped in late 2001 and in 2002, indicating a rise in labour market mismatch during that period.[27] This corresponds to the outward shift in the Beveridge curve in Figure 1.3. While the Beveridge curve shifts owing to changes in stock variables, primarily due to the long-term component of the unemployment rate, the rising frictions as indicated in parameter A concern flow variables. This implies that the matching function parameters may signal changes in mismatch and advance changes in stock variables as observed in the Beveridge curve.

6. Conclusions

In this paper we use the theoretical concepts of the Beveridge curve and the matching function to interpret cyclical and structural shocks in the economy using the empirical example of the Czech economy. While the Beveridge curve describes changes in the labour market using stock variables, the key relationship behind movements in the Beveridge curve is the matching function, which introduces flow variables into the analysis. The flows help us to explain shifts in the Beveridge curve, and we show that they can be used as predictors of business cycle turning points. From in-time intervention policy perspectives, the advantage of registry data in constructing coincidence indicators is that the data are comprehensive, published monthly with no delay, and not subject to revisions.

---

[25] We assume that the underreporting of vacancies does not change and that this effect is removed by first differencing. However, given that underreporting may increase with increasing mismatch, this introduced a negative bias into the vacancy coefficient estimates.

[26] On the other hand, through learning by doing and expanded use of cheap information technology and communication, labour offices should have improved the collection of data on vacancies over time.

[27] As we pointed out in Section 2.2, with total outflows as the dependent variable, the estimated decrease in A probably underestimates the deterioration in matching. For example, a decrease in overall outflows indicates an increasing mismatch between demand and supply, which implies a decreasing employment-to-inactivity outflow ratio. Outflows to jobs fall faster than overall outflows.

We show that movements in the UV space coincide with macroeconomic changes in the economy and that the Czech economy already exhibits features common in developed market economies. Our estimates of the matching function provide a better understanding of movements in the UV space. Changes in the parameters of the matching function allow us to distinguish cyclical and structural changes on the labour market. We trace some cyclical pattern in the unemployment inflow coefficient. Unlike the coefficient estimates, the fixed effects in the matching function reflect mismatches. Increases or decreases in fixed effects indicate an improvement or deterioration in the matching.[28] We show that omission of on-the-job search and discouraged worker effects from the model could in principle lead to biases, but we present at least indirect evidence that the scope of these effects is minor when discouraged workers are omitted. Provided that the measurement errors have a minor impact on the estimates, our results clearly indicate a deterioration in the functioning of the Czech labour market in recent years. Our findings support the view that outward shifts in the Beveridge curve are due to increasing mismatches.

This is probably the first study examining the matching function over the business cycle and using Czech vacancy flow data. Although the data and methodology we employ are far from what would be theoretically optimal and our estimates should be interpreted with caution, we give new insights into how the cyclical and structural components of the unemployment rate may be empirically separated. Such a distinction is crucial when interpreting observed changes in the economy. The insight we present here should be confronted with other, mostly macroeconomic approaches to the issue of structural and cyclical movements in the economy. From the perspective of the policy tools available in a small open EU economy, the (dis)functioning of the labour market is becoming more important with the enlargement of the monetary union. This makes labour market measures more important indicators and predictors of economic development. The framework we propose and explore in this paper should provide more comprehensive information than that revealed by individual labour market series.

[28] Given that the unemployment inflow rate is constant, changes in the additive term of the matching function may be associated with shifts in the Beveridge curve. On the contrary, changing unemployment inflows may also explain movements of the Beveridge curve, but they cannot affect our interpretation of the parameter changes in the matching function.

References

BERMAN, E. (1997): "Help Wanted, Job Needed: Estimates of a Matching Function from Employment Service Data." *Journal of Labour Economics* 15(1): S251–S292.

BLANCHARD, O. J., AND P. DIAMOND (1989): "The Beveridge Curve." *Brookings Paper on Economic Activity* 1: 1–76.

BURDA, M. C., AND S. PROFIT (1996): "Matching across Space: Evidence on Mobility in the Czech Republic." *Labour Economics* 3(3): 255–278.

COLES, M. G., AND E. SMITH (1998): "Marketplaces and Matching." *International Economic Review*, 39(1): 239–254.

HURNÍK, J., AND D. NAVRÁTIL (2005): "Labour Market Performance and Macroeconomic Policy: The Time-Varying NAIRU in the Czech Republic." *Czech Journal of Economics and Finance* 55(1–2): 25–40.

JACKMAN, R., C. PISSARIDES, AND S. SAVVOURI (1990): "Unemployment Policies and Unemployment in the OECD." *Economic Policy*, October: 449–490.

JURAJDA, Š., AND D. MÜNICH (2001): "Matching Skills in Transition." *CERGE-EI Discussion Paper No. 78.*

MÜNICH, D. (2001): "Job-seekers Matching and Duration of Unemployment in Transition." *CERGE-EI Discussion Paper No. 77.*

MÜNICH, D., J. ŠVEJNAR, AND K. TERRELL (1995): "Regional and Skill Mismatch in the Czech and Slovak Republics." in S. Scarpetta and A. Worgotter (eds.). *The Regional Dimension of Unemployment in Transition Countries – A Challenge for Labour Market and Social Policies*. Paris: OECD.

MÜNICH, D., J. ŠVEJNAR, AND K. TERRELL (1999): "The Worker-Firm Matching in Transition Economies: (Why) Are the Czechs more Successful Than Others?" *CERGE-EI Working Paper No. 141.*

PETRONGOLO, B., AND C. PISSARIDES (2001): "Looking into the Black Box: A Survey of the Matching Function." *Journal of Economic Literature* 39, June: 392–431.

PETRONGOLO, B., AND É. WASMER (1999): "Job Matching and Regional Spillovers in Britain and France." in M. Catin, J.Y. Lesieur, and Y. Zenou (eds.). *Developments Récents et Économie Spatiale: Employ, Concurrence Spatiale et Dynamiques Régionales*. Paris: Economica, 39–54.

PISSARIDES, C. (2000): *Equilibrium Unemployment Theory*, Cambridge, MIT Press.

WOOLDRIDGE, J. M. (2001): *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

CNB WORKING PAPER SERIES

2/2005	Kamil Galuščák: Daniel Münich	*Structural and cyclical unemployment: What can we derive from the matching function?*
1/2005	Ivan Babouček: Martin Jančar	*Effects of macroeconomic shocks to the quality of the aggregate loan portfolio*
10/2004	Aleš Bulíř: Kateřina Šmídková	*Exchange rates in the new EU accession countries: What have we learned from the forerunners*
9/2004	Martin Cincibuch: Jiří Podpiera	*Beyond Balassa-Samuelson: Real appreciation in tradables in transition countries*
8/2004	Jaromír Beneš: David Vávra	*Eigenvalue decomposition of time series with application to the Czech business cycle*
7/2004	Vladislav Flek, ed.:	*Anatomy of the Czech labour market: From over-employment to under-employment in ten years?*
6/2004	Narcisa Kadlčáková: Joerg Keplinger	*Credit risk and bank lending in the Czech Republic*
5/2004	Petr Král:	*Identification and measurement of relationships concerning inflow of FDI: The case of the Czech Republic*
4/2004	Jiří Podpiera:	*Consumers, consumer prices and the Czech business cycle identification*
3/2004	Anca Pruteanu:	*The role of banks in the Czech monetary policy transmission mechanism*
2/2004	Ian Babetskii:	*EU enlargement and endogeneity of some OCA criteria: Evidence from the CEECs*
1/2004	Alexis Derviz: Jiří Podpiera	*Predicting bank CAMELS and S&P ratings: The case of the Czech Republic*
12/2003	Tibor Hlédik:	*Modelling the second-round effects of supply-side shocks on inflation*
11/2003	Luboš Komárek: Zdeněk Čech Roman Horváth	*ERM II membership – the view of the accession countries*
10/2003	Luboš Komárek: Zdeněk Čech Roman Horváth	*Optimum currency area indices – how close is the Czech Republic to the eurozone?*
9/2003	Alexis Derviz: Narcisa Kadlčáková Lucie Kobzová	*Credit risk, systemic uncertainties and economic capital requirements for an artificial bank loan portfolio*
8/2003	Tomáš Holub: Martin Čihák	*Price convergence: What can the Balassa–Samuelson model tell us?*
7/2003	Vladimír Bezděk: Kamil Dybczak Aleš Krejdl	*Czech fiscal policy: Introductory analysis*
6/2003	Alexis Derviz:	*FOREX microstructure, invisible price determinants, and the central bank's understanding of exchange rate formation*

5/2003	Aleš Bulíř:	*Some exchange rates are more stable than others: Short-run evidence from transition countries*
4/2003	Alexis Derviz:	*Components of the Czech koruna risk premium in a multiple-dealer FX market*
3/2003	Vladimír Benáček: Ladislav Prokop Jan Á. Víšek	*Determining factors of the Czech foreign trade balance: Structural Issues in Trade Creation*
2/2003	Martin Čihák: Tomáš Holub	*Price convergence to the EU: What do the 1999 ICP data tell us?*
1/2003	Kamil Galuščák: Daniel Münich	*Microfoundations of the wage inflation in the Czech Republic*
4/2002	Vladislav Flek: Lenka Marková Jiří Podpiera	*Sectoral productivity and real exchange rate appreciation: Much ado about nothing?*
3/2002	Kateřina Šmídková: Ray Barrell Dawn Holland	*Estimates of fundamental real exchange rates for the five EU pre-accession countries*
2/2002	Martin Hlušek:	*Estimating market probabilities of future interest rate changes*
1/2002	Viktor Kotlán:	*Monetary policy and the term spread in a macro model of a small open economy*

CNB Research and Policy Notes

1/2005	David Navrátil: Viktor Kotlán	*The CNB's policy decisions – Are they priced in by the markets?*
4/2004	Aleš Bulíř:	*External and fiscal sustainability of the Czech economy: A quick look through the IMF's night-vision goggles*
3/2004	Martin Čihák:	*Designing stress tests for the Czech banking system*
2/2004	Martin Čihák:	*Stress testing: A review of key concepts*
1/2004	Tomáš Holub:	*Foreign exchange interventions under inflation targeting: The Czech experience*
2/2003	Kateřina Šmídková:	*Targeting inflation under uncertainty: Policy makers' perspective*
1/2003	Michal Skořepa: Viktor Kotlán	*Inflation targeting: To forecast or to simulate?*

CNB Economic Research Bulletin

May 2005	*Potential output*
October 2004	*Fiscal issues*
May 2004	*Inflation targeting*
December 2003	*Equilibrium exchange rate*

Czech National Bank
Economic Research Department
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 14 278
http://www.cnb.cz
e-mail: research@cnb.cz